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Haptic Softness Perception is Invariant to Surface Texture During Pressing

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***Abstract*—We investigated whether surface texture (i.e., stochastic roughness) influences softness perception during direct touch interactions with elastic, textured stimuli. Using a Bayesian adaptive modeling approach and a 2AFC task, we evaluated participants' ability to discriminate the softness of stimuli that varied in both their stochastic surface roughness (Hurst exponent) and material elasticity. To explore potential interactions between these features, we conducted two discrimination experiments, testing stimuli from two distinct ranges of elasticity. All participants performed the task using pressing. Results show that softness discrimination was determined primarily by material elasticity, with no discernible influence of surface features. The findings suggest that humans effectively isolate elasticity-based information from smaller-scale surface topography or texture during direct pressing with the finger.**

***Index Terms*—softness perception, texture and material perception, cue combination.**

I. Introduction

The haptic perception of softness (or hardness), often listed among the most salient dimensions of texture and material perception alongside roughness (or smoothness) [1]–[3], has been studied extensively. Physically, a material's softness can be expressed in terms of its elasticity (the ratio between stress and strain), stiffness or compliance (the ratio between applied force and displacement), or indentation hardness (resistance to indentation) [4]–[6]. The perceived softness of a material tends to be extracted using pressing or squeezing [7], but is sometimes available during other interactions, such as tapping or stroking [8]–[10]. During direct touch interactions, materials tend to be perceived as soft when their compliance is greater than the human finger, while stimuli in the stiffer range can still be perceived as soft with a rigid tool [9].

The importance of cutaneous cues for softness perception, such as information about the spatial deformation profile, has been stressed to a great extent [5], [9], [11]. When examining the relative weight of information for softness (i.e., hardness) discrimination, Bergmann Tiest and Kappers [5] showed that approximately 90% of the information is drawn from surface deformation cues and 10% from force/displacement cues. Similarly, stretching the skin of the fingertip immediately increases the perceived stiffness of materials [12]. The importance of local cutaneous cues has become particularly evident in studies using local anesthesia–without local cutaneous information from the finger, it is impossible for participants to discriminate between stimuli with a significant difference in stiffness, using pressing [11].

Although the haptic perception of softness has been studied extensively, in controlled experimental contexts, it has most frequently been investigated in isolation, that is, by manipulating material features (i.e., elasticity, stiffness, or hardness) to evaluate their role in softness perception. However, in the real world, changes in material features can co-occur with changes in other properties, such as surface features, and examining how attributes interact and conflict with one another is important [13]–[15]. In fact, research on softness perception has shown that *object shape* can sometimes influence perceived softness–for example during the pressing of curved surfaces [16] or the stroking of larger-scale (waved) topographies [17]. Given the essential role of cutaneous cues such as local skin deformation, it is conceivable that smaller-scale surface topography might also impact the perceived softness of objects.

The aim of this study was to investigate whether variations in smaller-scale surface structure or texture (specifically, stochastic roughness parametrized by the Hurst exponent) and material elasticity jointly influence softness perception during direct haptic explorations. The surface variations in our stimuli spanned feature changes between 30 and 500 µm, bridging both micro-, meso-, and macroscale features relative to a fingertip.

To ensure that our findings generalized across a broader range of elasticities, we conducted two discrimination experiments using naturalistic stimuli that systematically varied in stochastic roughness and elasticity. While the surface features

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of the stimuli were identical in both experiments, the elastic properties differed significantly: in Experiment 1, the stimuli were considerably stiffer than the human finger, whereas in Experiment 2, the stimuli had elasticity values close to those of a human finger.

We anticipated that participants would naturally use pressing as their primary exploratory mode to assess softness, consistent with prior findings [7]. We hypothesized that when pressing an elastic, textured stimulus with a finger, the surface texture might affect the way both the surface itself and the skin deform locally and, as a consequence, the perceived softness of the material.

To investigate potential interactions between surface features and material elasticity in shaping softness perception of our two-dimensional stimulus space, we used a two-alternative forced-choice (2AFC) task. However, traditional psychophysical methods would require exhaustive sampling, making the experiment overly long. We therefore employed the Adaptive Experimentation Psychology (AEPsych) framework, which implements non-parametric Bayesian inference techniques particularly suited for studying multidimensional perceptual judgments [18]–[20]. This approach enables efficient exploration of a continuous stimulus space through adaptive sampling, while its implementation of Gaussian Process models provides a convenient approach to modeling perceptual judgments and accommodating individual differences across participants. The framework's non-parametric approach furthermore avoids strong assumptions about the underlying psychometric function while constructing a complete model of the perceptual field, allowing us to examine sensitivity patterns across the full stimulus space.

II. Methods

A. Participants

*1) **Experiment 1**:* Thirteen healthy adult volunteers (7 women, 6 men; mean age = 27.47, SD = 9.54) participated in the study. Of these, one participant was left-handed and another participant was mixed-handed, while the remaining eleven participants were right-handed, as assessed using the Edinburgh Handedness Inventory [21]. The mixed-handed participant reported being right-handed and performed the experiment with their right index finger.

*2) **Experiment 2**:* Five healthy adult volunteers (2 women, 3 men; mean age = 32.2, SD = 2.05) participated in the study. All participants reported being right-handed and carried out the experiment with their right hand.

All participants gave their informed consent in writing prior to the study. The study was approved by the local ethics committee and carried out in accordance with relevant guidelines and regulations at Sorbonne Université and according to the Declaration of Helsinki.

B. Stimuli

*1) **Experiment 1**:* To study naturalistic surfaces while maintaining experimental control, we made use of our previously established haptic stimulus database in Experiment 1 [22]. This database comprises 49 stimuli that systematically vary in their material elasticity and stochastic surface roughness in controlled increments. Surface roughness was thus quantified using the Hurst exponent, which defines the self-similarity of surface height variations across multiple scales. A smaller Hurst exponent results in a slower decay towards small length scales and thus results in a higher micro-scale roughness (cf. Fig. 1). Changes in elasticity were achieved through different mixing ratios of 3D-printing material. This provided us with 49 stochastically rough, self-affine stimuli, systematically varying in their stochastic surface roughness (Hurst exponent) and material elasticity.

*2) **Experiment 2**:* In addition, for the second experiment, we created silicone replicas of the original surface textures using Ecoflex™ 00-30. This was done to achieve elasticities in the approximate range of the human fingertip itself. We first 3D-printed rigid molds using a Formlabs Form 3 Printer with gray resin, following specific anti-inhibition procedures for PDMS curing [23]. These molds were then used to cast the silicone samples with different mixing ratios, again resulting in 49 specimens (7 surfaces × 7 elasticities). After fabrication, the stimuli were measured with a shore-00 durometer on the center of the surface. Young's moduli were then calculated using Gent's conversion equation [6].

Fig. 1 shows height plots illustrating the effect of the Hurst exponent and photos of the final stimuli, while the elasticity and roughness parameters of both stimulus databases are summarized in Tables I, and II. All stimuli were coated in talcum powder before data collection to reduce differences in adhesion associated with different elasticities.

The most common interaction method to extract softness information is pressing [7]. The surfaces of our stimuli covered feature changes between 30 and 500 µm [22], some of which

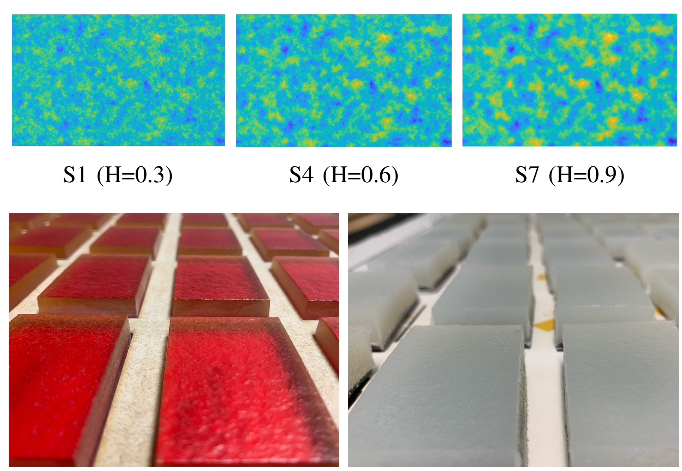

Fig. 1: Top: Height matrices illustrating the effect of the Hurst exponent on the stimuli. Bottom left: Low-elasticity stimuli taken from [22]. Bottom right: High-elasticity stimuli with the same surface statistics, but generated using Ecoflex™ 00-30.

should be clearly discernible by pressing [24], [25]. However, to ensure this, pilot testing of the stimuli confirmed that variations in both surface topography and material elasticity were discernible by pressing alone. From these pilot explorations, we found that the two stimulus sets did not have equivalent stimulus to perceptual step changes. For the low-elasticity stimuli, the space was separated by approximately one just-noticeable-difference (JND) per stimulus for both dimensions, while for the soft stimulus space, the JND distance depended on the dimension, with changes in the Shore values being slightly more discernible than changes in the Hurst exponent.

TABLE I: Surface parameters of both stimulus databases

Surface Nr.	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**
Hurst exponent	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Rq [$\times 10^{-2}$ mm]	5.68	5.16	4.79	4.51	4.30	4.14	4.01

TABLE II: Elasticity Parameters of Both Stimulus Databases

Low-elasticity set[a]							
Elasticity Nr.	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**
Shore-A value	24	25	26	29	34	44	66
Y. Modulus (MPa)	0.121	0.122	0.128	0.144	0.179	0.264	0.611
High-elasticity set[b]							
Elasticity Nr.	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**
Shore-00 value	9	18	25	32	39	43	47
Y. Modulus (MPa)	0.017	0.029	0.041	0.055	0.072	0.084	0.097

[a] The low-elasticity set was used in Experiment 1.
[b] The high-elasticity set was used in Experiment 2. Note the differing Shore scale between measurements of the two stimulus sets.

C. Apparatus

The participants were seated at a desk in front of a computer screen. During the experiment, they wore noise protection headphones to ensure that the feedback they received was purely haptic in nature. The light in the experimental room was dimmed, so that differences between the stimuli could not be seen, while the outline of the stimuli could still be made out for the targeted interactions. Stimuli were placed in front of the participant's dominant hand for free exploration with the index finger. A numpad was provided for responses via keypress on the side of the non-dominant hand of the participant.

D. Experimental Design and Procedure

Except for the stimulus set and the participants, Experiment 1 and 2 were identical. In the experiments, participants carried out a 2AFC discrimination task, in which they had to indicate which one of two stimuli felt softer. Before the experiment proper, four test trials of pre-chosen stimulus pairs were provided for participants to get acquainted with the task and stimulus space. Each trial began with a window appearing on the participant screen indicating "Which stimulus feels softer?". Participants were instructed to explore the stimuli freely, using any interaction methods they wanted [26], but only using their dominant index finger. They were asked to explore the left stimulus first and then move to the right stimulus. They were also asked not to explore the edges and corners of the stimuli and to avoid using their fingernails. Finally, they were asked to be consistent in their exploration method throughout the experiment once chosen in the test trials. Participants were encouraged to give quick and intuitive answers. Responses were given by keypress with the non-dominant hand. After each trial, the experimenter placed a new pair of stimuli in front of the participant, after which the task window reappeared on the participant's screen, indicating that they could begin with the next trial.

We used the adaptive experimentation framework AEPsych [18], [19] to model a single latent function F, which represents the perceptual scale underlying the comparison of stimuli:

$$P(\text{"A softer than B"}) = \Psi(F(A) - F(B))$$

Here, $F(A)$ and $F(B)$ represent the latent perceptual values assigned to stimuli A and B, respectively, and Ψ is a sigmoid or cumulative Gaussian function.

In contrast to the classical constant-stimulus procedure, which involves a grid search testing a fixed reference stimulus and only estimates specific thresholds in the stimulus space, AEPsych efficiently models the entire 2D-perceptual field. By using adaptive stimulus selection, AEPsych requires far fewer trials than exhaustively testing all (here 1225) possible stimulus comparisons. This is achieved using a Gaussian Process (GP) model, which serves as a probabilistic surrogate to estimate the latent perceptual function across the stimulus space. The GP model captures both the latent perceptual values and the associated uncertainty, enabling interpolation between tested points. Within this paradigm, response data from each trial are used to update the GP model in real-time. The framework then selects the next stimulus pair for the experiment, to balance exploration (sampling areas with high uncertainty) and exploitation (refining regions near decision boundaries), maximizing the information gained about the perceptual field. Each trial of the experiment thus entailed a new stimulus pair with a new combination of surface and elasticity parameters. A zero-mean GP prior was used, as we did not assume a specific function shape. Since this is a Bayesian optimization framework, model comparison metrics like Bayes factors do not apply.

Each of the two experiments consisted of 50 trials in total, a fixed number determined during pilot testing to ensure stable model convergence and to maintain consistency across participants while keeping the experiment duration reasonable ($\approx$ 30 minutes). Fig. 2 illustrates the experimental procedure.

III. Analysis

Statistical analyses of the discrimination data were conducted using Python (Anaconda Navigator, Spyder version 5.4.3) and using AEPsych [18], [19].

A Gaussian Process (GP) model [27] was fitted to the discrimination data for all participants. The model used Houlsby's [28] pairwise kernel for the Hurst and Shore values and an index kernel for participants. The model posterior distribution was estimated using variational inference [29], with hyperparameters fitted using maximum likelihood estimation. The Hurst and Shore values (cf. the corresponding values in Tables I–II) were scaled to the [0, 1] range using min-max normalization. Formally, given the binary nature of the outcome, we assumed each softness judgment, y, to be drawn from a Bernoulli distribution with probability $\Phi(f(u, v, p))$, where Φ is the Gaussian Cumulative Distribution Function (CDF), and $f(u, v, p)$ is a latent function over the model inputs: the left and right stimuli (given by their Hurst and Shore values) and the participant index.

$$y|f, u, v, p \sim Bernoulli(\Phi(f(u, v, p))) \tag{1}$$

We imposed a Gaussian Process (GP) prior on f. As is typical in GP regression, we used a constant mean function of zero, and we used a covariance function that is the product of two different covariance functions, k_{stim} and k_{part}.

$$f \sim GP(0, k_{\text{stim}} \cdot k_{\text{part}}) \tag{2}$$

The function k_{stim} models the covariance between pairs of stimuli. Given pairs $[a, b]$ and $[c, d]$, the covariance is given by

$$k_{\text{stim}}([a, b], [c, d]) = k(a, c) + k(b, d) - k(b, c) - k(a, d) \tag{3}$$

where k is the Matérn $5/2$ kernel (the derivation for this expression is provided by Houlsby et al. [28]). The function k_{part} is an index kernel, which models the covariance across participants.

Model fits were subsequently assessed using the area under the receiver operating characteristic curve (ROC AUC) [30]. To estimate the distribution of predictions, 10,000 samples were drawn and the ROC AUC was calculated.

IV. Results

Free exploration was permitted, but participants were instructed to remain consistent in their chosen strategy throughout the experiment. Observations by the experimenters confirmed that all participants naturally adopted and consistently used a pressing motion for the softness discrimination task in both experiments. No stroking or lateral movements were observed. The average trial duration (interaction with both stimuli) was 13.6 seconds in the first experiment and 8.3 seconds in the second, possibly reflecting that the discrimination of the high-elasticity stimulus set was somewhat easier.

A. *Experiment 1 (Low-Elasticity Set)*

Fig. 3 shows a histogram of the receiver operating characteristic curve (ROC AUC) scores for the model of Experiment 1.

The 99% highest-density interval (HDI) is the shortest interval in which 99% of the posterior mass lies, meaning that the ”true” ROC AUC lies within the bounds of the HDI with 99% certainty. As can be seen in Fig. 3, the HDI lies above 92%, which is generally considered to be an ”excellent” model fit [30].

We then modeled each participant individually in Experiment 1 and computed predicted response probabilities across a dense grid of the stimulus space defined by the Hurst and Shore values. Due to space constraints, only the group-level mean plot is shown in Fig. 4. However, the individual prediction surfaces were highly similar across participants, with only minor between-subject variability, justifying the mean visualization.

Fig. 4 illustrates the probability of any stimulus within our stimulus space being identified as softer compared to a central reference point for each participant. The black iso-contour lines symbolize the corresponding 25%, 30%, 40%, 50%, 60%, 75% 84%, and 96% probability lines, similar to just-noticeable-differences (JNDs). The overall quantity of and the spacing between the iso-contours in the space provide a picture of how precisely participants were capable of differentiating within the stimulus space. In Fig. 4, it is clearly evident that the softness discrimination was primarily determined by the Shore value,

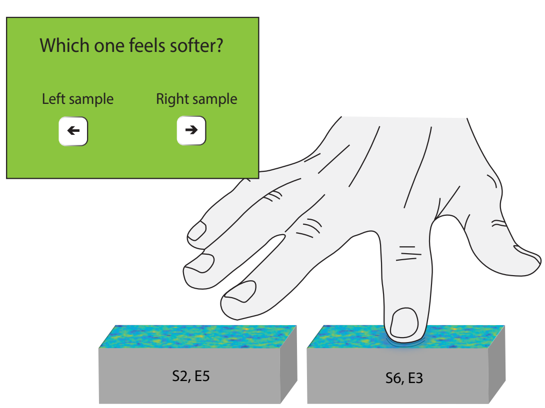

Fig. 2: Experimental procedure. Here with the example of stimulus S2,E5 and S6,E3 (cf. stimulus parameters in Tables I and II).

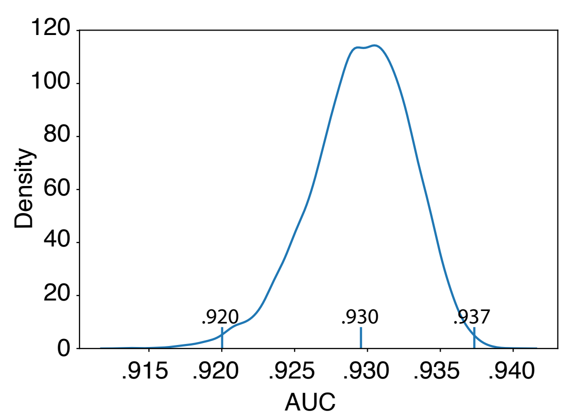

Fig. 3: The area under the receiver operating characteristic curve (ROC AUC) of the model for Experiment 1 carried out using the low-elasticity stimulus set. The mean of the distribution, as well as the limits of the 99% highest-density interval (HDI), are labeled.

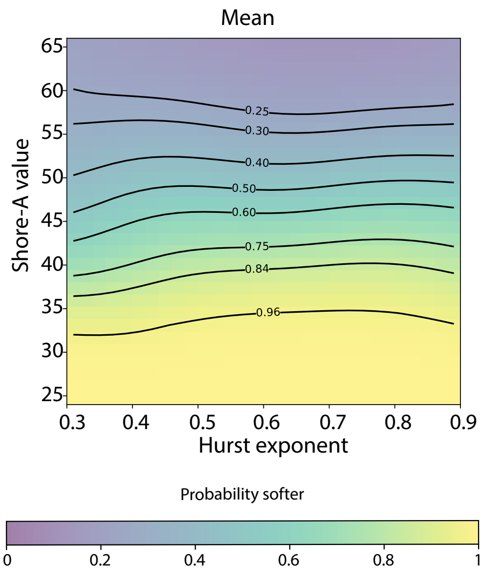

Fig. 4: Results for the low-elasticity set. Mean probability plot of model predictions for the 13 participants as a function of Hurst and Shore values to a central reference point (median Hurst and Shore value). Background color indicates the probability of a stimulus being chosen as softer compared to a stimulus with the medium Hurst and Shore values. The black iso-contour lines symbolize the 25%, 30%, 40%, 50%, 60%, 75%, 84%, and 96% probability lines. Individual participants showed similar perceptual fields, with only smaller between-subject variations, justifying the presentation of the mean visualization here.

with little influence of the Hurst exponent, since changes in probability are mainly observable across the vertical axis.

B. *Experiment 2 (High-Elasticity Set)*

The same analysis was repeated for the data from Experiment 2. Fig. 5 shows a histogram of the receiver operating characteristic curve (ROC AUC) scores for Experiment 2. As can be seen in Fig. 5, the HDI lies above 96.5%, indicating an "excellent" model fit [30]. As for Experiment 1, we then created model predictions for each participant. Because the five participants showed highly similar perceptual fields, we here only show the mean probability plot (cf. Fig. 6).

The mean psychometric field (Fig. 6) again demonstrates that the Shore value was the primary determinant of softness discrimination. Overall, iso-contours were spaced more closely to one another, compared to the low-elasticity stimulus set (Figure 4), indicating a slightly higher discriminability of the stimulus space.

C. *Discussion*

We conducted two experiments to explore the interaction between surface texture and material elasticity on softness perception. Contrary to our hypothesis, the results did not yield evidence of a notable influence of changes in surface

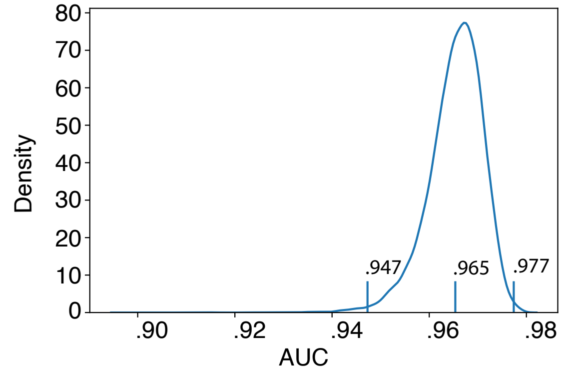

Fig. 5: The area under the receiver operating characteristic curve (ROC AUC) of the model for Experiment 2 carried out using the high-elasticity stimulus set. The mean of the distribution, as well as the limits of the 99% highest-density interval (HDI), are labeled.

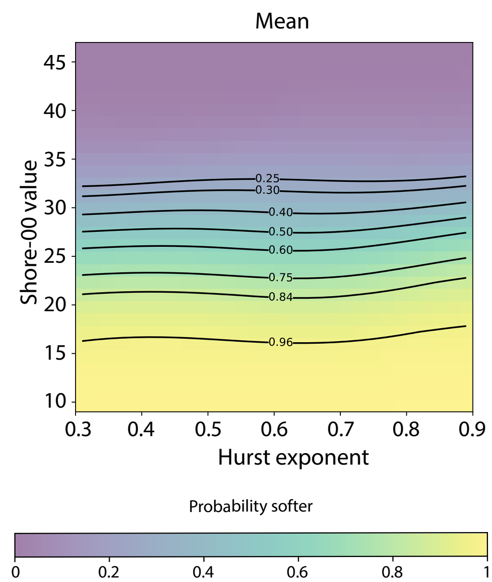

Fig. 6: Results for the high-elasticity set. Mean probability plot of softness model predictions across all participants as a function of Hurst and Shore values to a central reference point (median Hurst and Shore value). Background color indicates the probability of a stimulus being chosen as softer compared to a stimulus with the medium Hurst and Shore values. The black iso-contour lines symbolize the corresponding 25%, 30%, 40%, 50%, 60%, 75%, 84%, and 96% probability lines. Individual participants showed highly similar perceptual fields, justifying the presentation of the mean visualization.

roughness (Hurst exponent) on the perceived softness of either stimulus set. Perceptual judgments were largely dominated by the elasticity of the stimuli. Our results therefore suggest that changes in surface texture (as operationalized here, covering feature changes between 30 and 500 µm) do not affect the softness perception of elastic surfaces within the two ranges of elasticity tested.

This finding is interesting for several reasons. It is known that the perceived softness of a material is largely defined by local skin deformation and displacement [11], [31]–[33]. In the present study, changes in the topography of the stimuli through the Hurst exponent will likely have modified local skin deformation cues during the bare-finger interactions. One might thus have expected differing surface features to provide differential information about the material's elasticity. Specifically, local deformation of surface features (textons) upon pressing could theoretically have provided additional cues about the material's elasticity compared to a flat surface of the same material properties, as these features would deform differently based on the underlying material compliance. Furthermore, a larger evolution in the overall contact surface will likely have taken place from initial contact to maximal force applied on a rougher (smaller Hurst exponent) compared to a smoother or more flat (larger Hurst exponent) surface of the same elasticity. One could therefore have reasoned that, within a given range of elasticity, finer surface features (approaching a flat surface) might bias toward a harder percept, since the lack of prominent surface features (larger Hurst exponent) might provide less information about the deformability of the surface. However, this is not what we found. Our findings therefore suggest that participants were able to dissociate the perceived differences in surface features from their final softness judgments during pressing; thus avoiding a confounding influence of surface roughness on softness discrimination. While talcum powder was applied to minimize adhesion differences across all samples, we cannot fully exclude the possibility that subtle differences in surface adhesion may have covaried with elasticity.

This ability to dissociate surface features from elasticity is particularly noteworthy given that other types of surface geometry are known to influence softness perception. For instance, previous research has shown that the shape of a surface can affect its perceived compliance [16], [34], such that interactions with a convex surface yield a perceptual outcome equivalent to a harder stimulus whereas interactions with a concave surface yield a percept equivalent to a softer stimulus [16]. It is furthermore known that the evolution of the gross contact area provides information about the softness of a material [35] as well as the finger displacement relative to a surface [36], which in some instances can lead to confounding percepts of compliance and displacement [33]. Our findings therefore raise interesting questions about the spatial scale at which surface features transition from being "texture" to being processed as "shape" in the context of softness perception. Future research should systematically investigate this transition point by examining surfaces with progressively larger feature sizes or more pronounced textural elements.

Although Experiment 2 included only five participants, the perceptual fields estimated from their responses were remarkably consistent, suggesting that the observed pattern—namely, minimal influence of surface texture on softness discrimination—was not due to outlier behavior. Nevertheless, future work should confirm these findings in a larger sample. A further limitation of the study concerns the fabrication of the Ecoflex stimuli, which were less strictly controlled than the 3D-printed textures used in prior work. While the stimuli were visually inspected for potential air-bubbles or other inconsistencies, no profilometry or other surface measurements were carried out.

A final observation of the present study concerns participants' choice of exploration mode for the softness discrimination. Okamoto and Visell [10] have highlighted humans' ability to extract weak softness information from vibratory cues, and a line of further studies has demonstrated that vibrotactile information can affect the perceived object softness in certain contexts [37]–[39]. This especially becomes relevant during dynamic explorations of surfaces such as tapping or stroking of textured surfaces. It has, for instance, been shown that a lower surface friction leads to skin or skin-like materials feeling softer during stroking but not pressing [40]. However, participants consistently used pressing rather than stroking, verifying this as a preferred exploration strategy for extracting softness information [7], even when relevant cues might have been accessible during other exploration modes. The present research therefore makes no claims about the potential influence of surface features on softness perception during instructed dynamic explorations like sliding. Future research will have to investigate this, although the present study once more verifies the power of preferred exploration procedures to extract certain material qualities [7].

In summary, our study demonstrates that humans can effectively dissociate surface features from material elasticity during softness perception, with elasticity dominating the perceptual judgment during pressing interactions, regardless of concurrent variations in surface topography. This finding suggests that the human haptic system can isolate material properties even amid potentially conflicting surface cues.

References

[1] W. M. Bergmann Tiest and A. M. Kappers, "Analysis of haptic perception of materials by multidimensional scaling and physical measurements of roughness and compressibility," *Acta Psychologica*, vol. 121, no. 1, pp. 1–20, Jan. 2006. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0001691805000570

[2] M. Holliins, R. Faldowski, S. Rao, and F. Young, "Perceptual dimensions of tactile surface texture: A multidimensional scaling analysis," *Perception & Psychophysics*, vol. 54, no. 6, pp. 697–705, Nov. 1993. [Online]. Available: http://link.springer.com/10.3758/BF03211795

[3] S. Okamoto, H. Nagano, and Y. Yamada, "Psychophysical dimensions of tactile perception of textures," *IEEE Transactions on Haptics*, vol. 6, no. 1, pp. 81–93, 2013. [Online]. Available: http://ieeexplore.ieee.org/document/6216375/

[4] W. M. Bergmann Tiest, "Tactual perception of material properties," *Vision Research*, vol. 50, no. 24, pp. 2775–2782, Dec. 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0042698910004967

[5] W. Bergmann Tiest and A. Kappers, "Cues for Haptic Perception of Compliance," *IEEE Transactions on Haptics*, vol. 2, no. 4, pp. 189–199, Oct. 2009. [Online]. Available: http://ieeexplore.ieee.org/document/4906991/

[6] A. N. Gent, "On the relation between indentation hardness and young's modulus," *Rubber Chemistry and Technology*, vol. 31, no. 4, pp. 896–906, Sep. 1958. [Online]. Available: https://meridian.allenpress.com/rct/article/31/4/896/89954/On-the-Relation-between-Indentation-Hardness-and

[7] S. J. Lederman and R. L. Klatzky, "Hand movements: A window into haptic object recognition," *Cognitive Psychology*, vol. 19, no. 3, pp. 342–368, Jul. 1987. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0010028587900089

[8] K. Higashi, S. Okamoto, Y. Yamada, H. Nagano, and M. Konyo, "Hardness perception based on dynamic stiffness in tapping," *Frontiers in Psychology*, vol. 9, p. 2654, Jan. 2019. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6328787/

[9] R. M. Friedman, K. D. Hester, B. G. Green, and R. H. LaMotte, "Magnitude estimation of softness," *Experimental Brain Research*, vol. 191, no. 2, pp. 133–142, Nov. 2008.

[10] Y. Visell and S. Okamoto, "Vibrotactile Sensation and Softness Perception," in *Multisensory Softness: Perceived Compliance from Multiple Sources of Information*, ser. Springer Series on Touch and Haptic Systems, M. Di Luca, Ed. London: Springer, 2014, pp. 31–47. [Online]. Available: https://doi.org/10.1007/978-1-4471-6533-0_3

[11] M. A. Srinivasan and R. H. LaMotte, "Tactual discrimination of softness," *Journal of Neurophysiology*, vol. 73, no. 1, pp. 88–101, Jan. 1995. [Online]. Available: https://www.physiology.org/doi/10.1152/jn.1995.73.1.88

[12] M. Farajian, R. Leib, H. Kossowsky, T. Zaidenberg, F. A. Mussa-Ivaldi, and I. Nisky, "Stretching the skin immediately enhances perceived stiffness and gradually enhances the predictive control of grip force," *eLife*, vol. 9, Apr. 2020.

[13] K. Drewing and M. O. Ernst, "Integration of force and position cues for shape perception through active touch," *Brain Research*, vol. 1078, no. 1, pp. 92–100, Mar. 2006.

[14] M. O. Ernst and H. H. Bülthoff, "Merging the senses into a robust percept," *Trends in Cognitive Sciences*, vol. 8, no. 4, pp. 162–169, Apr. 2004. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364661304000385

[15] A. Frisoli, M. Solazzi, M. Reiner, and M. Bergamasco, "The contribution of cutaneous and kinesthetic sensory modalities in haptic perception of orientation," *Brain Research Bulletin*, vol. 85, no. 5, pp. 260–266, Jun. 2011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0361923010002698

[16] J. Hartcher-O'Brien, B. Edin, and V. Hayward, "Shape-elasticity tactile confound," in *Hand, Brain and Technology: The Somatosensory System CSF Conferenc*, 2018, p. 1. [Online]. Available: https://ethz.ch/content/dam/ethz/special-interest/hest/rehabilitation-engineering-lab-dam/images/Events/HBT2018/HBT_2018_Conference_Booklet.pdf

[17] Q. Sun, J. Guo, and S. Okamoto, "Effects of surface textures and shapes on perceived softness of hard materials," *International Symposium on Affective Science and Engineering*, vol. ISASE2022, no. 0, pp. 1–4, 2022. [Online]. Available: https://www.jstage.jst.go.jp/article/isase/ISASE2022/0/ISASE2022_1_3/_article

[18] L. Owen, J. Browder, B. Letham, G. Stocek, C. Tymms, and M. Shvartsman, "Adaptive nonparametric psychophysics," *arXiv*, Apr. 2021, arXiv: 2104.09549. [Online]. Available: http://arxiv.org/abs/2104.09549

[19] J. Browder, S. Bochereau, F. van Beek, and R. King, "Stiffness in Virtual Contact Events: A Non-Parametric Bayesian Approach," in *2019 IEEE World Haptics Conference (WHC)*. Tokyo, Japan: IEEE, Jul. 2019, pp. 515–520. [Online]. Available: https://ieeexplore.ieee.org/document/8816102/

[20] X. D. Song, K. A. Sukesan, and D. L. Barbour, "Bayesian active probabilistic classification for psychometric field estimation," *Attention, Perception, & Psychophysics*, vol. 80, no. 3, pp. 798–812, Apr. 2018. [Online]. Available: http://link.springer.com/10.3758/s13414-017-1460-0

[21] R. C. Oldfield, "The assessment and analysis of handedness: The Edinburgh inventory," *Neuropsychologia*, vol. 9, no. 1, pp. 97–113, Mar. 1971. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0028393271900674

[22] K. K. Driller, C. Fradet, V. Hayward, and J. Hartcher-O'Brien, "Conception and Design of a Dual-Property Haptic Stimuli Database Integrating Stochastic Roughness and Elasticity," in *Haptics: Understanding Touch; Technology and Systems; Applications and Interaction*, H. Kajimoto, P. Lopes, C. Pacchierotti, C. Basdogan, M. Gori, B. Lemaire-Semail, and M. Marchal, Eds. Springer Nature Switzerland, 2024, pp. 223–237.

[23] B. Venzac, S. Deng, Z. Mahmoud, A. Lenferink, A. Costa, F. Bray, C. Otto, C. Rolando, and S. Le Gac, "PDMS curing inhibition on 3D-printed molds: why? Also, how to avoid It?" *Analytical Chemistry*, vol. 93, no. 19, pp. 7180–7187, May 2021, publisher: American Chemical Society. [Online]. Available: https://doi.org/10.1021/acs.analchem.0c04944

[24] M. Hollins and S. R. Risner, "Evidence for the duplex theory of tactile texture perception," *Perception & Psychophysics*, vol. 62, no. 4, pp. 695–705, May 2000.

[25] M. Hollins and S. J. Bensmaïa, "The coding of roughness," *Canadian Journal of Experimental Psychology = Revue Canadienne De Psychologie Experimentale*, vol. 61, no. 3, pp. 184–195, Sep. 2007.

[26] T. Callier, H. P. Saal, E. C. Davis-Berg, and S. J. Bensmaia, "Kinematics of unconstrained tactile texture exploration," *Journal of Neurophysiology*, vol. 113, no. 7, pp. 3013–3020, Apr. 2015.

[27] C. E. Rasmussen and C. K. I. Williams, *Gaussian processes for machine learning*, ser. Adaptive computation and machine learning. Cambridge, Mass: MIT Press, 2006, oCLC: ocm61285753.

[28] N. Houlsby, F. Huszár, Z. Ghahramani, and M. Lengyel, "Bayesian active learning for classification and preference learning," *ArXiv*, Dec. 2011, arXiv:1112.5745 [cs, stat]. [Online]. Available: http://arxiv.org/abs/1112.5745

[29] D. M. Blei, A. Kucukelbir, and J. D. McAuliffe, "Variational inference: A review for statisticians," *Journal of the American Statistical Association*, vol. 112, no. 518, pp. 859–877, Apr. 2017, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01621459.2017.1285773. [Online]. Available: https://doi.org/10.1080/01621459.2017.1285773

[30] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, Jun. 2006. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016786550500303X

[31] C. Dhong, R. Miller, N. B. Root, S. Gupta, L. V. Kayser, C. W. Carpenter, K. J. Loh, V. S. Ramachandran, and D. J. Lipomi, "Role of indentation depth and contact area on human perception of softness for haptic interfaces," *Science Advances*, vol. 5, no. 8, p. eaaw8845, Aug. 2019, publisher: American Association for the Advancement of Science. [Online]. Available: https://www.science.org/doi/10.1126/sciadv.aaw8845

[32] S. C. Hauser and G. J. Gerling, "Force-rate cues reduce object deformation necessary to discriminate compliances harder than the skin," *IEEE Transactions on Haptics*, vol. 11, no. 2, pp. 232–240, Apr. 2018, conference Name: IEEE Transactions on Haptics. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7949145

[33] A. Moscatelli, M. Bianchi, A. Serio, A. Terekhov, V. Hayward, M. Ernst, and A. Bicchi, "The change in fingertip contact area as a novel proprioceptive cue," *Current Biology*, vol. 26, no. 9, pp. 1159–1163, May 2016. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0960982216301348

[34] C. Xu, Y. Wang, and G. J. Gerling, "An elasticity-curvature illusion decouples cutaneous and proprioceptive cues in active exploration of soft objects," *PLOS Computational Biology*, vol. 17, no. 3, p. e1008848, Mar. 2021, publisher: Public Library of Science. [Online]. Available: https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1008848

[35] A. Bicchi, E. Scilingo, and D. De Rossi, "Haptic discrimination of softness in teleoperation: the role of the contact area spread rate," *IEEE Transactions on Robotics and Automation*, vol. 16, no. 5, pp. 496–504, Oct. 2000. [Online]. Available: http://ieeexplore.ieee.org/document/880800/

[36] E. R. Serina, E. Mockensturm, C. D. Mote, and D. Rempel, "A structural model of the forced compression of the fingertip pulp," *Journal of Biomechanics*, vol. 31, no. 7, pp. 639–646, Jul. 1998.

[37] A. Ikeda, T. Suzuki, J. Takamatsu, and T. Ogasawara, "Producing Method of Softness Sensation by Device Vibration," in *2013 IEEE International Conference on Systems, Man, and Cybernetics*, Oct. 2013, pp. 3384–3389, iSSN: 1062-922X. [Online]. Available: https://ieeexplore.ieee.org/document/6722330

[38] J. Kildal, "3D-press: haptic illusion of compliance when pressing on a rigid surface," in *International Conference on Multimodal Interfaces and the Workshop on Machine Learning for Multimodal Interaction*, ser. ICMI-MLMI '10. New York, NY, USA: Association for Computing Machinery, Nov. 2010, pp. 1–8. [Online]. Available: https://doi.org/10.1145/1891903.1891931

[39] Y. Visell, B. L. Giordano, G. Millet, and J. R. Cooperstock, "Vibration influences haptic perception of surface compliance during walking," *PloS One*, vol. 6, no. 3, p. e17697, Mar. 2011.

[40] N. Arakawa, N. Saito, and S. Okamoto, "Less frictional skin feels softer in a tribologically paradoxical manner," *IEEE Access*, vol. 10, pp. 55 279–55 287, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9775937/